Evaluation of Bluetooth Properties for Indoor Localisation

Khuong Nguyen and Zhiyuan Luo

Abstract Current indoor localisation systems make use of common wireless signals such as Bluetooth, WiFi to track the users inside a building. Amongst those, Bluetooth has been widely known for its low-power consumption, small maintenance cost, as well as its wide-spread amongst the commodity devices. Understanding the properties of such wireless signal definitely aids the tracking system design. However, little research has been done to understand the properties of Bluetooth wireless signal amongst the current Bluetooth-based tracking systems. In this chapter, the most important Bluetooth properties related to indoor localisation are experimentally investigated from a statistical perspective. A Bluetooth-based tracking system is proposed and evaluated with the location fingerprinting technique to incorporate the Bluetooth properties described in the chapter.

Keywords Indoor localisation · Bluetooth properties · Location fingerprinting

1 Introduction

Indoor localisation is the state-of-the-art to identify and observe a moving human or object inside a building. Global Positioning System (GPS) has long been an optimal solution for outdoor localisation, yet the indoor counterpart remains an

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open research problem because the sophisticated building infrastructure hinders the GPS signal, as well as making indoor signals modelling difficult. The 10 m limitation accuracy of the GPS is another consideration for those looking to apply the technology, as 1–2 m accuracy is desirable for room-level tracking.

Within the past decade, there have been numerous attempts to solve the problem with extensive hardware implementations such as the Active Badge system (Want et al. 1992; Addlesee et al. 2001), the Cricket system (Priyantha 2005) which measure the time-of-flight from a tag to the beacons using ultrasonic sensors. Despite an extreme accuracy up to 3 cm, 95 % of the time, these systems are expensive and hard to maintain and deploy. There have been pure software solutions such as Fingerprinting to utilise the built-in Wireless LAN of the building to create a signal-to-position mapping database beforehand, then applies pattern-matching algorithms to filter the most probable position for a real-time signal fingerprint (Bahl and Padmanabhan 2000; Youssef and Agrawala 2005; Brunato and Kallo 2002; Lin and Lin 2005). The Wireless LAN signal, however, uses much power, and is hard to install and configure in the first place. Another alternative is the Bluetooth wireless signal, which has been widely known for its low-power consumption, small maintenance and installation cost, as well as its ubiquitous amongst the commodity devices, such as mobile phones, head phones and laptops. There have been many Bluetooth-based indoor tracking systems (Orozco-Ochoa et al. 2011; Wang et al. 2011; Frost et al. 2012; Bargh and Groote 2008), yet, those systems did not pay much attention to the Bluetooth properties and assumed they are similar to other wireless signal. Understanding the properties of the wireless signal definitely aids the tracking system design. In this chapter, the most important Bluetooth properties related to indoor localisation are experimentally investigated from a statistical perspective. We aim to answer the question: Is Bluetooth signal robust enough for the indoor localisation purpose? In addition, a Bluetooth-based tracking system is proposed and evaluated with the location fingerprinting technique to incorporate the Bluetooth properties described in this chapter. The performance of such system is compared to the RADAR indoor tracking's counterpart, which is one of the first indoor tracking systems (Bahl and Padmanabhan 2000).

The contribution of this chapter is two folds. First, we investigate the most important Bluetooth properties from an indoor localisation perspective. Second, we propose a novel Bluetooth-based indoor tracking system to incorporate the Bluetooth properties demonstrated in this chapter.

2 Localisation with the Wireless Signal

Wireless signal is ubiquitous now-a-days, and benefits many indoor tracking applications. This section outlines the application of wireless signal into localisation and compares Bluetooth technology with Wireless LAN, which are the most popular wireless signal, in terms of localisation perspective.

2.1 Fine-Grained Tracking and Coarse-Grained Tracking

Based on the station broadcasting range, whenever an user and a station can communicate, which means they are in range, the user location can be interpreted as the station location itself. This method is known as proximity-based tracking. Despite its simplicity, the solution has two drawbacks. First, the system accuracy is exactly the broadcasting range of the station. A Class 2 Bluetooth device has a 10 m range, which is not very useful for indoor localisation. This method is enhanced by dividing the tracking space into grids. The stations are strategically placed in such a way that each grid block is overlapped by the signal from as many different stations as possible (Fig. 1). Thus, instead of coarsely predicting the user's location to be somewhere within the station's broadcasting range, the accuracy is improved by interpreting the user's location to be inside the overlapped area.

The idea still has one flaw, since many stations must be deployed to have a good tracking result. The coarse-grained tracking idea is great for observing users at room-level resolution. However, to identify an user location at sub-room-level up to 1–2 m, a more fine-grained tracking is needed. The solution can be further enhanced by analysing the wireless signal between each station to the user's unknown location. This idea bases on the fact that the wireless signal attenuates and gets weaker as it travels in the air. There are two measurements to roughly represent the distance between an user and a station: the received signal strength indication (RSSI) and the link quality (LQ). A simple, yet efficient method known as Location Fingerprinting makes use of these measurements. It utilises the built-in wireless signal of the building to create a signal-to-position mapping database beforehand, then applies pattern-matching algorithms to filter the most probable position for a real-time signal fingerprint. In comparison to proximity-based tracking, this solution offers much higher fine-grained tracking even with a few stations. In the next section, we discuss the difference between Bluetooth and Wireless LAN, which are the most popular wireless signals, for the purpose of fine-grained indoor localisation.

2.2 A comparison of Bluetooth and Wireless LAN

Bluetooth technology is a means for devices to wirelessly communicate over short distances. Many tracking systems require the user to carry 'a tag' for observation. However, the users often forget to wear it, making localisation impossible.

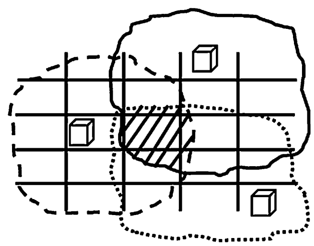


Fig. 1 Overlapping signal of 3 stations

Table 1 Bluetooth classes comparsion

	Working range (m)	Power consumption (mW)
Class 1	100	100
Class 2	10	2.5
Class 3	1	1

Compared to WiFi, Bluetooth technology has been more widely adopted amongst the commodity hardware such as mobile phones, head phones and laptops, which is a benefit as almost everyone carries a mobile phone these days. For large scale deployment, the ease of installation and the affordability also make Bluetooth-based approach stand out. Two Bluetooth devices are virtually ready to communicate upon plugging in, while a Wireless LAN network requires an adapter, and a router/wireless spot, which also needs more configuration. Further, the low cost (£3/Belkin dongle) is an advantage, which also consumes as little as 2.5 mW for a Class 2 dongle, compared to 1,675 mW for a Wireless LAN card while transferring data (Chandra 2003), which is 670 times higher in power consumption. Table 1 compares the power consumption level of the three Bluetooth classes. Class 2 Bluetooth is widely used nowadays, while Class 3 Bluetooth devices are obsolete and are no longer manufactured.

One big problem for any signal-based indoor tracking system is the attenuation of the wireless signal in the air. To increase the signal robustness, Bluetooth employs the ‘adaptive frequency hopping’ technique, in which the transceiver hops through 79 channels 1,600 times per second, while avoiding those channels with high interference. The transmission is broken down into very small packets to increase the signal robustness. Although both Bluetooth and WiFi use the license-free 2.4 GHz spectrum, WiFi devices stick to one channel during the session. The robustness of the adaptive frequency hopping technique will be investigated in this chapter.

However, when it comes to real-time tracking, WiFi offers almost instant RSSI and LQ inquiry, while a Bluetooth device takes 10.24 s for a full scan. Although it is possible to quickly target a particular user with the Bluetooth’s MAC address to perform a direct connection request, 1.28 s are still needed to determine whether the user is within range (Hay and Harle 2009). This weakness can be compensated by either modifying the Page Scan parameter of the Bluetooth dongle; or using more than one ‘scanner’ to boost the discovery rate. Table 2 summaries the difference between Bluetooth and Wireless LAN technology, in terms of indoor localisation perspective.

3 Properties of Bluetooth Signal at a Static Position

This section surveys the Bluetooth properties from a statistical perspective. We discuss what have been learned and how to benefit them in the actual implementation.

Table 2 Bluetooth and wireless LAN comparsion

	Bluetooth	Wireless LAN
Indoor range	10 m	100 m
Power consumption	2.5 mW	1,675 mW
Data transfer	Frequency hopping	Sequence spreading
Frequency	2.4 Ghz	2.4 Ghz
Ease of usage	Simple	Complex
Cost	Low (£3/dongle)	High (£20/card)
Inquiry time	1.28 s (direct inquiry)	Instant

3.1 The Distribution of Bluetooth Signal

Figure 2 shows the histogram distribution of the Bluetooth signal in a clear area with 30 cm distance between the transmitter and the receiver. We sampled the RSSI reading every 10.24 s over 24 h with a total of 8,897 samples. This is the standard Bluetooth inquiry rate. We recorded 52 histogram distributions over 4 months, with 96 % of the histogram samples showed a near-Gaussian distribution, 82 % of those were left-skewed, 11 % of those were almost-symmetric, and only 7 % were right-skewed. This skewness should be considered when modelling the indoor Bluetooth signal. Other indoor WiFi survey reports a similar distribution pattern (Kaemarungsi and Krishnamurthy 2004). The range of Bluetooth RSSI can be as wide as 10 dBm, with very few isolated individual RSSI, which is similar to the WiFi indoor signal. Since the histogram contains a concentrated peak around the highest RSSI value, with a high 50 % probability, it is possible to average the whole distribution as a single RSSI value, which performs well for Weighted K-nearest neighbour's algorithm.

These experiments used a Belkin Class 2 Bluetooth dongle. However, other dongles were tested to show a similar result.

3.2 The Antenna Orientation of the Bluetooth Device

An important property of the Bluetooth signal strength is the direction the device is facing. To the best of our knowledge, by surveying the internal design of popular Class 1 and Class 2 branded Bluetooth dongles in the market (Belkin, BlueNext, Nexxus, Asus, BlueWalker, Daffodil, Kensington, StarTech) from different Bluetooth chip manufacturers (Broadcom, Cambridge Silicon Radio (CSR), Texas Instruments (TI)), none of the current Bluetooth dongle is equipped with an omnidirectional antenna. The Bluetooth antenna is physically shaped as a plate (Fig. 3), which broadcasts the wireless signal in a cone-shaped wave. The broadcasting angle is around 30°, and is highly concentrated at the centre. Therefore, it is understandable that the RSSI is strongest when two devices are totally parallel and opposite each other.

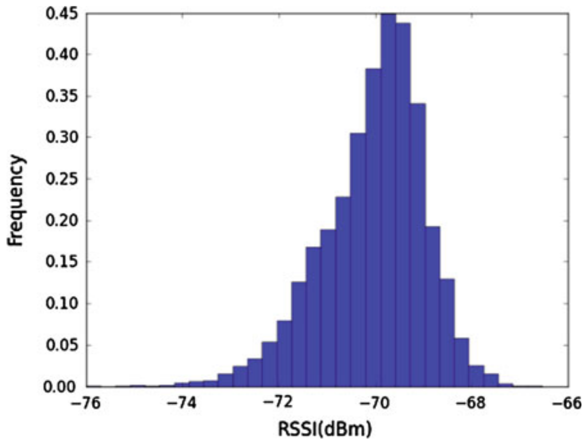


Fig. 2 Bluetooth RSSI distribution

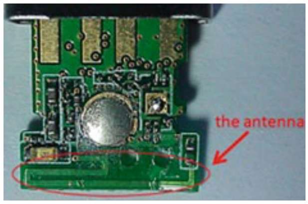


Fig. 3 Belkin dongle's antenna

To study the change of the Bluetooth signal upon the antenna orientation, we divide the 2D space into eight directions, parallel to the floor. At a clear distance of 30 cm between two opposite devices at the same height, the signal variation can be as large as 10 dBm (Fig. 4). The RSSI gradually decreases when one device rotates from the West-side to the East-side, with the weakest RSSI observed at the furthest East-side.

By moving one device out of the 30° broadcasting range of the other device, the signal variation still behaves as expected, although it is not as clear as when they are totally opposite each other (Fig. 5). A similar result was observed when changing the device's altitude.

Based on this observation, it is recommended that the Bluetooth stations to be placed at the corners, with the antenna pointing towards the centre of the room for the best signal broadcasting.

3.3 *The Variation of the Bluetooth Signal upon Distance*

When an user is further away from a fixed station, the attenuation weakens the wireless signal. However, it is not possible to fit a mathematical equation to calculate the exact signal strength loss, given the distance. We can only expect a

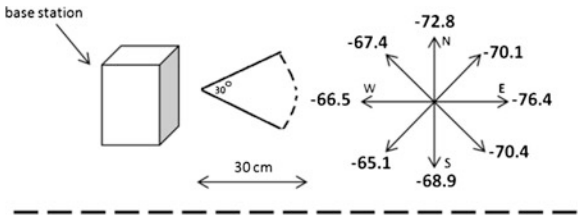


Fig. 4 RSSI orientation at the same height, opposite each other

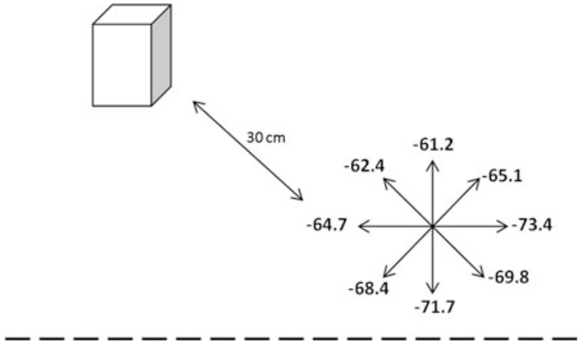


Fig. 5 RSSI orientation at the same height, not opposite each other

rough decreasing pattern as the distance increases. In general, the changes of Bluetooth RSSI can be separated into two categories; given the user can move a short or a long distance.

3.3.1 Small Scale Variation

It is not surprising that a very small distance on the order of a wavelength can cause the Bluetooth signal to vary to as much as 10 dBm. Small-scale variation is caused mostly by the multipath effect. When the two devices can directly see each other, the strongest signal follows a shortest unobstructed straight line-of-sight from one end to the other. However, in an indoor environment with many obstacles, the signal propagates in different paths because of reflection, scattering, diffraction and eventually reaches the destination (Fig. 6).

It was suggested measuring the readings every few metres apart to avoid capturing this variation (Youssef and Agrawala 2005). However, it makes the tracking capability very coarse with probabilistic algorithms such as the Bayesian approach, since they predict the unknown real-time location to be just one of the

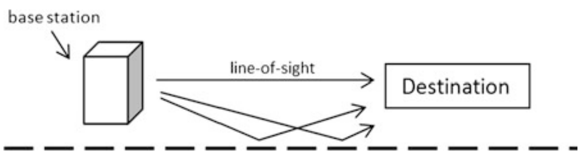


Fig. 6 Multipath fading

records in the database. Another solution is based on the Weighted K-nearest neighbour algorithm, which takes the average weighted measurements of K locations, and returns an estimated position in the middle of these K locations. The best solution is increasing the resolution of the tracking grid, such as taking measurements every 10 cm, which increases the system's maximum accuracy to 10 cm. However, this process is very time-consuming and results in a bigger database. We solve this issue with a robot to automatically collect the data, to be discussed later.

3.3.2 Large Scale Variation

When the user moves a long distance, it is expected that the signal strength gets weaker gradually. For the purpose of coarse-grained tracking, this serves as a warning that the user is leaving the tracking area. The large scale variation is very important for any fine-grained tracking purpose, as there is a correlation between the signal strength and the travelling distance at any location. However, the complex indoor structure makes modelling the wireless signal a very difficult and inaccurate task. Two distinct indoor locations further apart might have a similar signal strength pattern, due to multipath and other signal fading issues. This problem is alleviated by setting up many stations to increase the signal density and the uniqueness of each location in the tracking zone. We analyse this variation in details in both 2D and 3D spaces.

3.3.3 Moving Horizontally and Parallel to the Floor

In an ideal world, by ignoring all atmospheric, water absorption and multipath, an RF signal fades as it propagates in the air, because of the free-space path loss exclusively. The signal strength loss is calculated by the Friis transmission equation

$$P_{RX} = P_{TX} \cdot G_{TX} \cdot G_{RX} \cdot \left(\frac{\lambda}{4\pi d} \right)^2 \tag{1}$$

with

P_{TX}	Transmission power of sender
P_{RX}	Remaining power of wave at receiver
G_{TX}	Gain of transmitter
G_{RX}	Gain of receiver
λ	Wave length
d	Distance between sender and receiver

Since the Bluetooth RSSI has a near-normal distribution shape, the large scale variation will be represented under a log-normal random variable. We fit a best

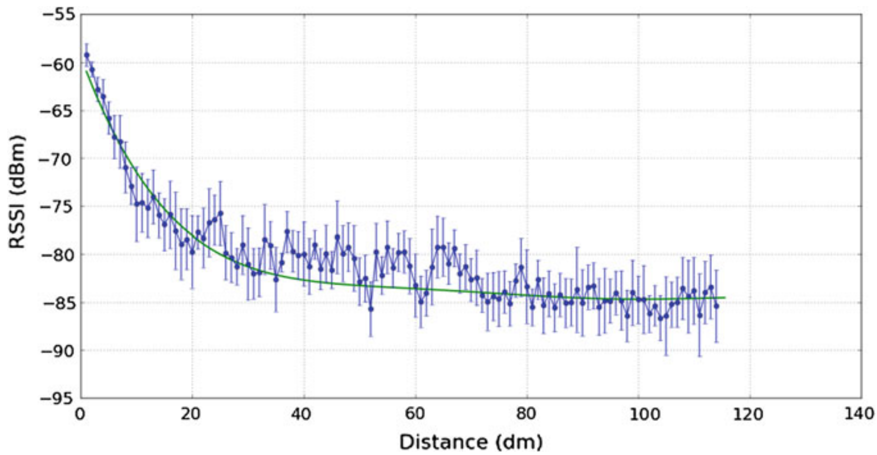


Fig. 7 Large scale variation

line to present the median path loss, calculated by the above formulae. This best fit line shows a quadratically decreasing relationship between the distance and the RSSI.

The above experiment (Fig. 7) was taken in a long office corridor, so that a clear unobstructed line-of-sight is possible. The base station was placed in the middle of the corridor and the Bluetooth device was gradually moving perpendicularly further away from the station. Overall, when the distance is more than 70 cm, we would expect to see a significant change in the RSSI. Interestingly, we found out from approximately 5 m onward, the RSSI stays almost the same. The signal is completely lost amongst all the noises at a distance of 6 m for a Class 2 Bluetooth device, which supposes to have a working range of 10 m. Another feature observed from Fig. 7 is that the standard deviation of the Bluetooth signal grows bigger as the distances increases. However, the number of recorded RSSI decreases as the distance increases. We conclude that strong Bluetooth RSSIs, which are found near the station, are more stable. Further, it is strongly recommended to set up a Bluetooth station every 5 m for the best Bluetooth signal differentiation amongst locations.

3.3.4 Moving Vertically and Perpendicularly to the Floor

Does the altitude of the device influence the Bluetooth signal? Many indoor tracking systems do not implement this feature, as they assume the height of the transceiver is fixed throughout the tracking process. This is not correct, as an user can carry his phone, which is used as the tracking tag, in either his shirt pocket or trouser's pocket. Further, the change of the signal strength upon the altitude is important for 3D tracking to detect if the user is moving upstair or downstair.

First, the range an user carries his tag can vary from 70–145 cm off the ground for an adult. Does this 75 cm difference influence the signal strength? In this experiment, a fixed station was set up at 1 m off the floor. The distance between the station and the device is 50 cm. When moving the device from the bottom floor to 2 m off the floor, the RSSI gradually increased. When the Bluetooth device and the station were parallel and opposite each other at the same height around 1 m off the ground, the highest RSSI were observed. The signal strength gradually decreased when the altitude of the device continued to increase.

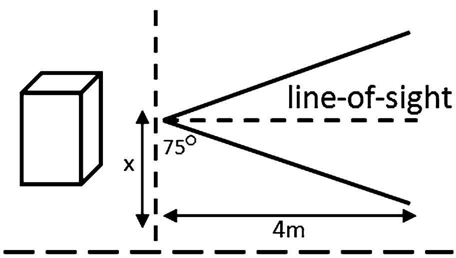
Further, to investigate the effect of the altitude upon the Bluetooth station, the above experiment was repeated with the station set up at different heights, from the bottom floor to 1 m off the floor. Interestingly, we encountered many strange individual RSSIs with significant larger or smaller value, when the station was set up just 10 cm above the ground. This phenomenon can be explained by the effect of the multipath fading. The Bluetooth signal travels in different directions upon reflection, scattering, diffraction off the indoor objects and reaches the destination in different paths. Occasionally, two in-phase Bluetooth waves meet in the air, and cause a constructive interference, if both of them are using the same frequency. Destructive interference happens when two out-phase waves happen to be on the same channel, in which they will cancel each other. A station placed near the ground will increase the chance of two Bluetooth waves meeting in the air. We experimentally found out that the above phenomenon is less severe when the station's altitude is higher than 1 m off the floor (Fig. 8).

Since Sect. 3.2 reveals that the effective broadcasting angle of the Bluetooth device is around 30°, and Sect. 3.3 shows that the signal strength is strongly distinguishable within 4 m distance, the effective altitude of the Bluetooth station is calculated as

$$\mathrm{x} = \left[\frac{4}{\tan(75)}\right] = 1.07\,(\mathrm{m}) \tag{2}$$

Thus, it is strongly recommended to set up the base stations at least 1 m off the ground to lessen the multipath problem.

Fig. 8 Station's optimal altitude



4 Properties of Bluetooth Signal on a Mobile User

Tracking a mobile user is harder than tracking a static one. First, the 10.24 s discovery time of the Bluetooth devices is not suitable for real-time tracking. Second, the user's movement pace affects the robustness of the received signal as reported for the Wireless LAN (Kaemarungsi and Krishnamurthy 2004). The first issue is alleviated in the recent 'connection-based' approach, which reduces the discovery time to 1.28 s, following a one-off registration of the device's MAC-ID. The second problem is more difficult, because the hang-over effect makes the wireless signal unpredictable.

It was reported that the faster the walking speed, the less reliable the Bluetooth signal strength is (Madhavapeddy and Tse 2005). To verify this statement, we recorded the RSSI at two moving paces more accurately with a robot: 2 m/s for a fast walk and 0.22 m/s for a slow walk. Figure 9 shows that the difference between 'fast walk' and 'slow walk' in our experiment was much less severe than what reported above. However, we did observe a similar increasing pattern of the standard deviation, as the distance from the station increases. Further, contrast to the report that 'static measurements' failed to achieve a better result than 'slow walk', we observed a similar performance in both cases. 'Static measurement' means the robot stops for a few seconds to take readings before moving on.

There are two differences between our approach and the one reported above. First, we applied the recent connection-based inquiry to measure the RSSI in less than 1.28 s, rather than using the standard 10.24 s inquiry, which allowed us to collect more RSSI at a faster rate. Second, we opted for the RSSI measurement while the other experiment used the LQ as the signal strength measurement. The use of a robot to collect data could also have an impact in our case.

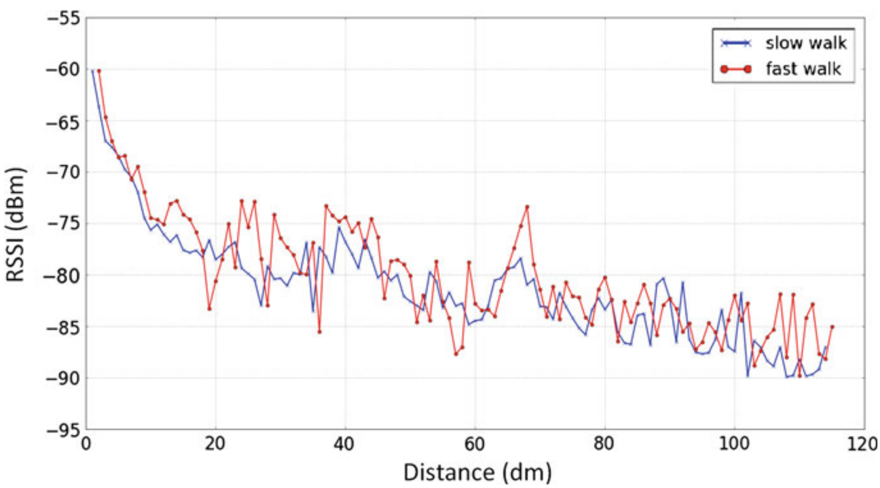


Fig. 9 Comparison of walking speeds

5 External Influences upon the Bluetooth Signals

Many indoor tracking systems assumed an ideal environment (Bruno and Delmastro 2003; Hallberg et al. 2003). In reality, the surrounding varies from time to time due to human movements, humidity, furniture re-arrangement, etc. Any database-based tracking system must frequently update the latest signal readings, or use multiple databases to reflect different environments during rush hour, early morning, late evening.

5.1 Influence from the Human Body

The human presence is a major factor for any indoor tracking system. The human body contains as much as 75 % of water, which absorbs the radio wireless signal. Many tracking systems require the user to carry a tag, which lies very close to the human body. To examine the human presence effect, two fixed base stations were set up at 1 m away in a cafeteria. Two periods of time were chosen to record the Bluetooth signal: when the cafeteria was crowded with people at mid-noon and when it was quiet in the late evening. Figure 10 below shows that the Bluetooth signal fluctuates more wildly when there are many people around, with a bigger standard deviation of 3.17, compared to 2.36 without the human presence.

We attempted the above experiment at the same location with the Wireless LAN to compare the signal variation. Interestingly, the standard deviation recorded for the Wireless LAN was bigger than the value recorded for the Bluetooth signal when the area was crowded. We observed both the WiFi and Bluetooth signals for a week with different levels of crowd. All our records showed that the Bluetooth wireless signal copes well with much noise around. However, when the distance between the two stations increased, the Wireless LAN signal was much stable with smaller standard deviation. This phenomenon shows that in a noisy environment, the Bluetooth signal is much more adaptive for short distance communication than the Wireless LAN, by breaking the transmission into small packets and frequently switching channels to avoid signal collision.

5.2 Influence Amongst the Bluetooth Signals

Deploying a Bluetooth-based tracking system involves setting up many Bluetooth stations under the same domain. Do the Bluetooth signals affect each other? Is there a relationship amongst the signals over times? This section discusses whether many Bluetooth devices can co-exist in a small domain. Since the limited Bluetooth broadcasting range demands a close distance between stations, the potential signal collision is a possibility.

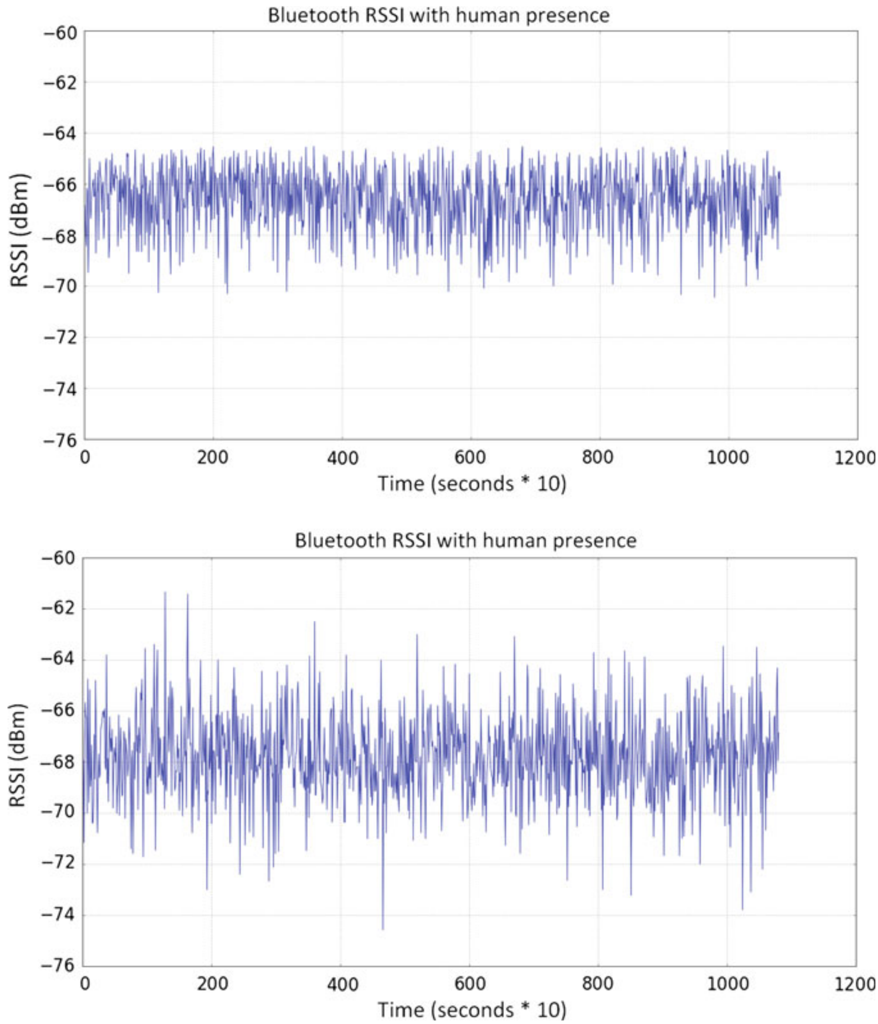


Fig. 10 Bluetooth RSSI without/with human presence

5.2.1 The Correlation of the Bluetooth RSSI at the Same Station

An indoor tracking system relying on an off-line database has to capture the signal variation in different times of the day to reflect different environments. Is it necessary to re-run the whole surveying process at the same time in different days, presuming the environment does not change as much? This condition can only be relaxed if the Bluetooth signals themselves do not cause any internal conflict. We applied the Wide-Sense Stationary (WSS) process to verify the stationary property of the Bluetooth RSSI in different times at the same station, assuming the environment is static. A Bluetooth RSSI is said to be stationary, if its histogram

Table 3 6 h segments comparsion

	6–12am	12–6pm	6pm–0am	0–6am
Mean	−67.5	−67.74	−68.1	−66.86
Standard deviation	1.14	1.04	1.09	0.95

distribution do not change with time. Two conditions must be met. First, the mean value of the RSSI distribution is a constant, regardless of the time. Second, the autocorrelation function of the WSS process is independent of the time difference at the same station. With an RSSI sequence recorded in an isolated room to eliminate most external noises over 24 h, we divided the sequence into chunks of 6 h, and compared these segments. Table 3 shows that the means and the standard deviation of the four sequences were very close, which mostly satisfies the first WSS condition. Despite our best effort to eliminate the surrounding noises, it is difficult to purify the environment, which explains the small difference in the statistical values.

Figure 11 demonstrates the correlogram of the above 6 h segments. Beside the close autocorrelation, the shapes of the 4 correlograms were also very identical. We also tested different segment sizes of 1, 2, 4, 8 and 12 h to confirm the similarity of the result. Therefore, we conclude that the Bluetooth RSSI at the same station is independent, regardless of the time difference, presuming the environment is identical.

5.2.2 The Correlation of the Bluetooth Signal at Different Stations

Section 3.3 reveals that the Bluetooth signal is completely lost amongst all the noises at a distance of 6 m onwards. The short distance characteristic of the Bluetooth signal demands the Bluetooth stations to be set up as close as 5 m to each other, which raises the question if they can potentially interfere. We set up 4 stations as shown in the first testbed (Sect. 6.1). A receiver R was placed at the lower left corner of the room to record the signal from the 4 stations over 24 h. Table 4 shows that there is no correlation between the received signal, with a strong distinction of the mean, standard deviation and the correlation. We conclude that the Bluetooth signal in different stations is independent.

5.3 Influence from Other Wireless Sources

It is common to have many wireless sources co-existing in the same environment. Bluetooth technology increases the signal's robustness by adapting the frequency-hopping to constantly switching between 79 channels 1,600 times per second to avoid collision with other wireless signals operating on the same 2.4 GHz spectrum, such as Wireless LAN, microwave oven. Some indoor tracking systems were

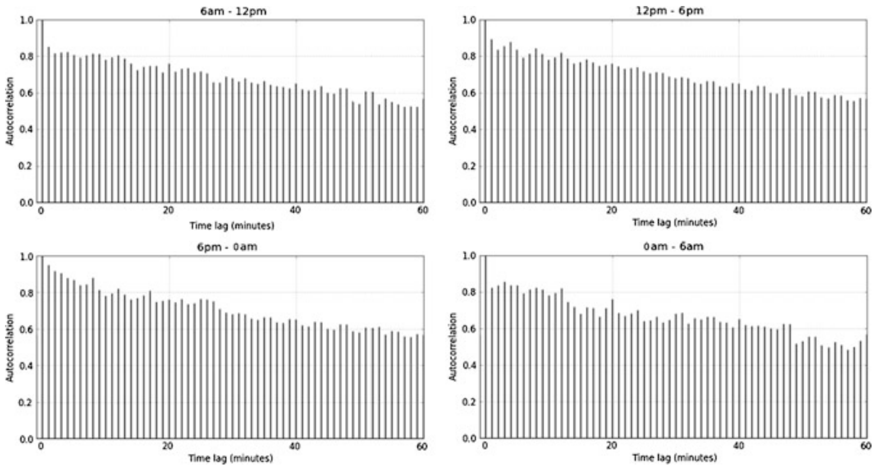


Fig. 11 6 h segments correlograms

Table 4 Signal correlation from 4 different stations

	Distance (m)	Mean	Standard deviation	Correlation
R–A	5	−82	2.84	−0.21
R–B	5.8	−86	3.28	−0.17
R–C	4	−78	2.4	+0.17
R–D	1.5	−69	1.57	+0.26

seen to in-corporate both Bluetooth and Wireless LAN (Pandya et al. 2003), yet there has not been a verification to confirm if there is any conflict between the Bluetooth and Wireless LAN signals.

To test the influence of the Wireless LAN upon the Bluetooth signal, a Bluetooth transmitter and receiver were set up to constantly measure the RSSI between them. The same environment was artificially modified by injecting many WiFi signal, with five computers equipped with the wireless LAN cards constantly ping each other. Table 5 shows that both cases have a very identical mean value and standard deviation. There is also a strong correlation R = 0.92. Therefore, we conclude that the interference caused by the Wireless LAN is almost non-existent.

6 A Bluetooth-Based Location Fingerprinting System

To incorporate the above Bluetooth features, we propose a Bluetooth-based indoor tracking system with the Fingerprinting method. Especially, to tackle the hassle of database collection, we designed a robot to automatically collect the Bluetooth data. Three classification algorithms were implemented, the Weighted K-nearest

Table 5 Bluetooth distribution with/without WiFi noises

	Mean	Standard deviation
Without WiFi	−71	2.45
With WiFi	−72	2.7

neighbours, the Bayesian approach and the Histogram matching algorithm. We compared our system performance to the RADAR system (Bahl and Padmanabhan 2000), which used a similar K-nearest neighbours approach with the Wireless LAN signal.

6.1 Data Collection

The system was installed in two different locations as described below. In both cases, a robot was used to collect the Bluetooth data along with the location's physical co-ordinate.

6.1.1 Testbed 1

The first testing environment was deployed on the second floor in the Computer Lab, University of Cambridge where we used the Bat system as a reference to provide accurate 3D location data. This testbed was, however, limited to just a single room of 15 m^2 (5 × 3 m). All locations within the tracking zone can be seen by all four Bluetooth stations (Fig. 12).

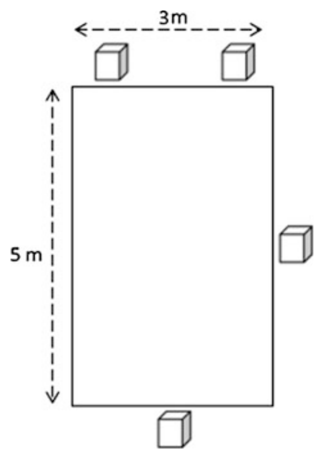


Fig. 12 First testbed

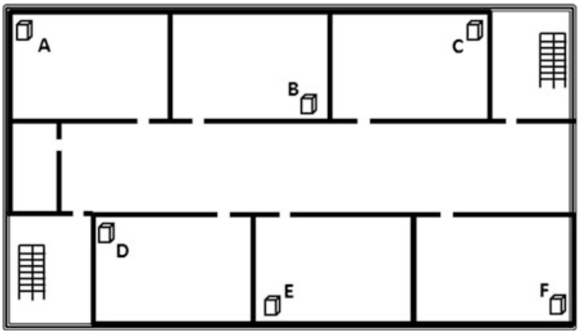


Fig. 13 Second testbed

6.1.2 Testbed 2

The second testbed aimed to deploy the system in a large environment, where each station alone cannot cover the whole tracking zone. An office of 136 m^2 (17 × 8 m) was used to deploy the system (Fig. 13).

6.1.3 Automated Robot

For a database reference method such as Fingerprinting, the system accuracy depends on the reliability of the reference entries stored in the database, as well as the number of surveyed entries. Yet, it takes much effort for a human to survey every location within the tracking area. For this reason, a robot was built from LEGO pieces (Fig. 14), which is convenient for maintenance and re-production. The robot is capable of carrying a laptop for 8 h per single charge. More details about the robot are discussed in (Nguyen 2011). The advantages of the mobile robot for indoor localisation include automated data collection, less interference with RF signals due to its small size, and adjustable body to experiment at different heights. Although in real-time tracking, an user will present instead of a robot, the signal attenuation due to human body can be compensated.

6.2 System Evaluation

We collect data from 260 random positions in the first testbed and 270 positions in the second testbed. Each position contains the Bluetooth RSSI fingerprint, and the physical 3D co-ordinate. To evaluate the system performance, we provide the Bluetooth fingerprint into the system, which returns a predicted co-ordinate based on the training database constructed beforehand. Three algorithms were implemented.

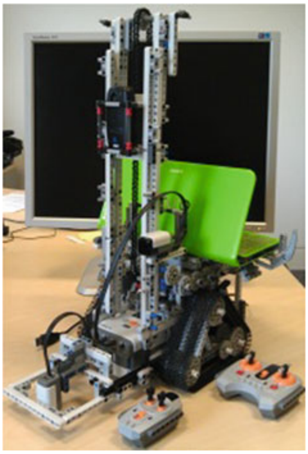


Fig. 14 LEGO robot

6.2.1 Weighted K-Nearest Neighbours

Given a Bluetooth RSSI, the Weighted K-nearest neighbour's algorithm selects K-nearest entries in the database, in terms of the Euclidean distance. A Bluetooth RSSI is represented as an n-tuple $X = (x_1, x_2, \ldots, x_n)$, with x_i is the signal strength measured from the station i. The 'distance' between two Bluetooth RSSI X and Y is measured as

$$\mathrm{dist}(X, Y) = \sqrt{(x_1 - y_1)^2 + \cdots + (x_n - y_n)^2} \tag{3}$$

It is common that many distinct locations far away might have a similar combination of signal strength, because of the indoor signal multipath problem, where the wireless signal bounces off the indoor objects and arrives at the destination in different paths. Thus, by considering the 'weight', corresponding to the inverse distance between each neighbour n_i and the unknown position l, the final estimated 3D position $E = (e_x, e_y, e_z)$ would be much more accurate. The reason to invert the distance is to prioritise closer neighbours over further away one. The 'weighted' equation is repeated for each dimension of the unknown location $L = (l_x, l_y, l_z)$

$$e_x = \frac{\sum_{i=1}^{K} \frac{1}{\mathrm{dist}(n_i, l)} l_x}{\sum_{i=1}^{K} \frac{1}{\mathrm{dist}(n_i, l)}} \tag{4}$$

Finally, an optimal K parameter is calibrated specifically for each environment and the wireless signal. In our system, we experimentally found $K = 16$ as an optimal value across all testing points. Some locations had better results with different K. Generally, starting from $K = 1$, which is equivalent to considering only the nearest entry, the accuracy tends to increase when K increases, up to a certain point ($K = 16$ in our case), then it begins to decrease with bigger K.

Compared to the normal K-nearest neighbour algorithm implemented in the early version of the RADAR system, the overall performance was enhanced by more than 25 % (Fig. 15).

6.2.2 Naive Bayesian Approach

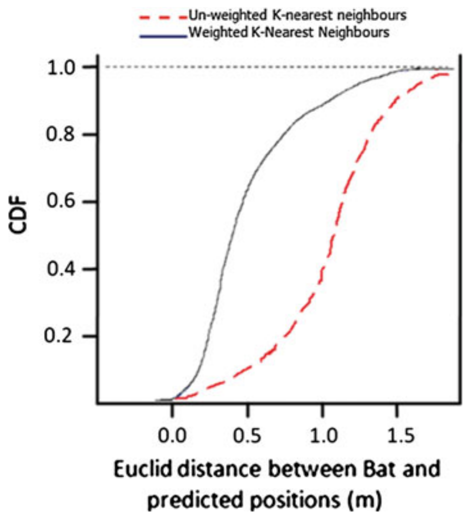
While the Weighted K-nearest neighbour's algorithm computes an average of all nearest locations to estimate an unknown position, the Bayesian approach picks up just one entry in the database with the highest probability to represent the estimated location. The idea of 'probability' comes from a histogram table, which records the Bluetooth signal variation in terms of the small-scale variation. Assuming the base stations are independent, the probability of a given signal strength pattern $X = (x_1,\ x_2,\ldots,x_n)$ at a particular location L recorded in the database is calculated by the probability of each individual signal strength x_i, as follows

$$P((x_1, x_2, \ldots, x_n)|L) = P(x_1|L)\, P(x_2|L)\ldots P(x_n|L) \tag{5}$$

Each separate term $P(x_i|L)$ can be calculated independently based on the frequency of x_i recorded at the location L in the database

$$P(x_i|L) = \frac{\text{number of times } x_i \text{ appears}}{\text{total number of readings at location } L} \tag{6}$$

Fig. 15 Weighted K-NN versus unweighted K-NN



However, the actual purpose is to calculate the probability that the given RSSI $X = (x_1, x_2,\ldots,x_n)$ indeed belongs to the location L recorded in the database. This is the reverse probability

$$P(L|(x_1, x_2, \ldots, x_n)) = \frac{P((x_1, x_2, \ldots, x_n)|L)\,P(L)}{P(x_1, x_2, \ldots, x_n)} \tag{7}$$

The probability $P((x_1, x_2,\ldots,x_n) \mid L)$ is calculated using Eq. 5. The probability $P(L)$ of a location L itself is always $1/N$ with N = number of entries in the database, which is a constant. The probability $P(x_1, x_2,\ldots,x_n)$ is the number of times $(x_1, x_2,\ldots, x_n)$ appears in the database divided by the total number of entries in the database, which is also a constant. Thus, $P(L)$ and $P(x_1, x_2,\ldots,x_n)$ can be ignored in the computation.

To sum up, given an unknown location's signal strength pattern, the probability of every record L_i in the database $P(L_i \mid (x_1, x_2,\ldots,x_n))$ to match this unknown location is calculated. The position L_i with the highest probability is considered as the estimated position.

This Naive Bayesian approach assumes the base stations are independent. This assumption is correct as discussed in Sect. 5.2. The drawback of this solution was the big size of the database, resulting from many readings taken at a fixed position to record the signal variation. Second, the tracking zone's resolution determines the accuracy of this approach. For every 1 m measurement, the Bayesian approach cannot provide estimated position with more than 1 m accuracy, because it picks just one entry in the database as the estimated location. Ideally, we prefer a high granularity database, yet it consumes much longer to survey the tracking zone. In general, the Bayesian approach performs better than the Weighted K-nearest neighbour's counterpart, as it takes into account the signal variation, at the cost of a bigger database size.

6.2.3 Histogram Matching

The Histogram matching method adapts a similar approach as the Bayesian, by using the histogram table. Besides, it takes a further step by considering the signal variation at the unknown position too, while the Bayesian approach considers just a single RSSI snapshot. However, this solution has one flaw. Although it is possible to wait for signal arriving in the database construction stage, in real-time tracking, the mobile user moves quickly, which limits the amount of signal received at any particular moment. For tracking static user, this approach shows very good performance.

To compare the histogram tables, we implemented two algorithms. The 'Student's *T* test' is performed, if the histogram table is normally distributed, otherwise the 'Kolmogorov–Smirnov test' (K–S test) is performed. Section 3.1 implies that the Bluetooth signal strength does not have a Gaussian distribution only 4 % of the times. The experimental result shows that the performance does not degrade too much by this violation.

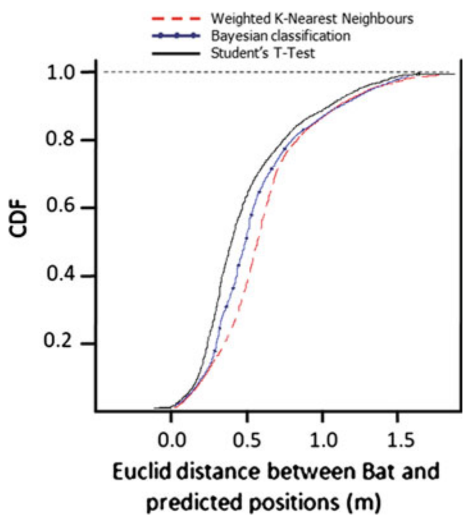
6.2.4 Performance Summary

In general, all three algorithms performed equally well (Fig. 16).

The Weighted K-nearest neighbours is simple and easy to implement, but deciding the optimal K parameter is challenging, which can only be achieved experimentally depending on the environment deployed and the wireless signal's properties. The histogram matching approach seems to edge out of the other two, since it uses the signal variation in both off-line and on-line stages. However, obtaining many readings in a short period of time during real-time tracking is challenging, especially for the Bluetooth signal. The Bayesian approach algorithm captures just one signal strength reading during real-time tracking, but considers the whole range of the signal variation recorded in the database to select one entry with the highest probability as the estimated location. This is the most balanced algorithm, in terms of performance and realistic deployment. The system achieved less than 1.5 m error, 88 % of the time; or 50 cm error, 43 % of the time. Compared to the RADAR system with 2 m error using the Wireless LAN signal, this performance is very promising, considering the affordability and the efficiency nature of the Bluetooth devices. It only took less than 0.04 s to estimate an unknown position on a 1.6 GHz computer.

The Bayesian approach can be further enhanced by combining with the Weighted K-nearest neighbours. Instead of picking just one location in the database, it selects K entries with the highest probabilities, and uses the probability measurement as the weight to average the estimated position. However, it would take more computational power to process K entries.

Fig. 16 System performance



7 Conclusions and Further Work

In this chapter, we investigated the Bluetooth properties for the indoor localisation purpose. The Bluetooth signal is strongly immune to the interference caused by other wireless sources, thanks to the adaptive frequency hopping. However, human presence is a major factor, which influences the Bluetooth signal strength and deviation. Compared to the Wireless LAN, Bluetooth technology has the benefits of affordability and efficiency, which suit the purpose of ubiquitous deployment. The main weakness of Bluetooth, however, is the slow inquiry time, which can take up to 10.24 s for a full scan. The recent 'connection-based' approach has reduced it to just 1.28 s, which is very important for tracking mobile users.

We implemented a Bluetooth-based indoor tracking system with Fingerprinting method and a robot to incorporate the Bluetooth properties learned from this chapter. The system performance is promising with an accuracy of less than 1.5 m error, 88 % of the time, considering the affordability and efficiency nature of the Bluetooth technology. We plan to implement machine learning algorithms to tackle the slow inquiry time, as well as minimal the signal-survey effort.

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